

# Improved estimator of the entropy and goodness of fit tests in ranked set sampling

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## Abstract

The entropy is one of the most applicable uncertainty measures in many statistical and engineering problems. In statistical literature, the entropy is used in calculation of the Kullback-Leibler (KL) information which is a powerful mean for performing goodness of fit tests. Ranked Set Sampling (RSS) seems to provide improved estimators of many parameters of the population in the huge studied problems in the literature. It is developed for situations where the variable of interest is difficult or expensive to measure, but where ranking in small sub-samples is easy. In This paper, we introduced two estimators for the entropy and compare them with each other and the estimator of the entropy in Simple Random Sampling (SRS) in the sense of bias and Root of Mean Square Errors (RMSE). It is observed that the RSS scheme would improve this estimator. The best estimator of the entropy is used along with the estimator of the mean and two biased and unbiased estimators of variance based on RSS scheme, to estimate the KL information and perform goodness of fit tests for exponentiality and normality. The desired critical values and powers are calculated. It is also observed that RSS estimators would increase powers.

**Keywords:** Ordered Ranked set sampling; Judgement ranking; Order statistic; Information theory; Exponential; Normal; Uniform

## 1 Introduction

Suppose a continuous random variable  $X$  has cumulative distribution function (cdf)  $F(x)$  and a probability density function (pdf)  $f(x)$ . The differential entropy  $H(f)$  of the random variable  $X$  is defined to be

$$H(f) = - \int_{-\infty}^{\infty} f(x) \log f(x) dx. \quad (1)$$

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The entropy is one of the most applicable uncertainty measures in many statistical and engineering problems. In statistical literature, the entropy is used in calculation of the Kullback-Leibler (KL) information which is a powerful mean for performing goodness of fit tests. The Kullback-Leibler (K-L) information of  $f(x)$  against  $f_0(x)$  is defined in [7] to be

$$I(f; f_0) = \int_{-\infty}^{\infty} f(x) \log \frac{f(x)}{f_0(x)} dx. \quad (2)$$

Since  $I(f; f_0)$  has the property that  $I(f; f_0) \geq 0$ , and the equality holds if only if  $f = f_0$ , the estimate of the K-L information has also been considered as a goodness of fit test statistic by some authors including [2] and [5]. It has been shown in the aforementioned papers that the test statistics based on the K-L information perform very well for testing exponentiality [5] as compared, in terms of power, with some leading test statistics.

Ranked Set Sampling (RSS) has been developed by McIntyre (1952). This method is applied for situations in which measuring a variable is costly or difficult, but where ranking in small subsets is easy. In this method, we first subdivide a sample of size  $n = k^2$  randomly into  $k$  subsamples of size  $k$ , rank each subsample visually or using any simple or cheap method and then in the  $r^{\text{th}}$  subsample, measure and record only the unit of rank  $r$  which is denoted by  $X_{r:k}^{(r)}$  ( $r = 1, \dots, k$ ). Since the subsamples are independent,  $X_{r:k}^{(r)}$ 's are independent random variables. Also the marginal distribution of  $X_{r:k}^{(r)}$  is the same as that of  $r^{\text{th}}$  order statistic from a sample of size  $k$  of  $X$ , i.e.  $X_{r:k}$ . As it was proved by McIntyre, mean of this sample is an unbiased estimator of the mean of  $Y$  with an efficiency slightly less than  $\frac{1}{2}(k+1)$ , relative to the mean of a Simple Random Sample (SRS) of size  $k$ . Thus “ranked set sampling should be useful when the quantification of an element is difficult but the elements of a set are easily drawn and ranked by judgment.” (Dell and Clutter 1972).

This method was also extended to estimating variance (Stokes 1980a), correlation coefficient (Stokes 1980b) and the situations in which the sample is subdivided into subsamples of different sizes.

In This paper, we introduced two estimators for the entropy and compare them with each other and the estimator of the entropy in Simple Random Sampling (SRS) in the sense of bias and Root of Mean Square Errors (RMSE). It is observed that the RSS scheme would improve this estimator. The best estimator of the entropy is used along with the estimator of the mean and two biased and unbiased estimators of variance based on RSS scheme, to estimate the KL information and perform goodness of fit tests for exponentiality and normality. The desired critical values and powers are calculated. It is also observed that RSS estimators would increase powers.

## 2 Entropy estimation

The nonparametric estimation of the entropy

$$H = \int_0^1 \log \left( \frac{dF^{-1}(p)}{dp} \right) dp. \quad (3)$$

Table 1: Simulated Minimum RMSE (MRMSE) and Minimum Absolute Bias (MAB) of  $H_{mn}^1$  and  $H_{mn}^2$  and optimal  $m$  for  $k = 10$  and three distributions with different values of  $r$ .

		$r$			
		2	3		
		$H_{mn}^1$	$H_{mn}^2$	$H_{mn}^1$	$H_{mn}^2$
U(0,1)	MRMSE (optimal $m^*$ )	0.062(8)	0.081(5)	0.045(11-13)	0.073(5)
	MAB(optimal $m^*$ )	0.030(10)	0.047(5)	0.021(15)	0.048(5)
e(1)	MRMSE (optimal $m^*$ )	0.157(5)	0.168(4)	0.125(6)	0.140(4)
	MAB(optimal $m^*$ )	0.001(6)	0.0137(5)	0.004(7)	0.014(5)
N(0,1)	MRMSE (optimal $m^*$ )	0.184(5,10)	0.246(5)	0.138(7,8)	0.233(5)
	MAB(optimal $m^*$ )	0.113(10)	0.205(5)	0.062(12)	0.206(5)

$$^*m = 1(1)k/2 \text{ for } H_{mn}^2 \text{ and } m = 1(1)rk/2 \text{ for } H_{mn}^1$$

An estimate of (3) can be constructed by replacing the distribution function  $F$  by the empirical distribution  $F_n$ . The derivative of  $F^{-1}(i/n)$  is estimated by  $(x_{i+w:n} - x_{i-w:n})n/(2w)$ . The estimate of  $H$  is then

$$H(m, n) = \frac{1}{n} \sum_{i=1}^n \log \left( \frac{n}{2m} (x_{i+m:n} - x_{i-m:n}) \right), \quad (4)$$

where the window size  $m$  is a positive integer, which is less than  $n/2$ , and  $x_{i:n} = x_{1:n}$  for  $i < 1$ , and  $x_{i:n} = x_{n:n}$  for  $i > n$ .

Ebrahimi et al. (1994) proposed a modified sample entropy as

$$H_c(n, m) = n^{-1} \sum_{i=1}^n \log \frac{n}{c_i m} (X_{(i+m)} - X_{(i-m)}) \quad (5)$$

where

$$c_i = \begin{cases} 1 + \frac{i-1}{m} & \text{if } 1 \leq i \leq m \\ 2 & \text{if } m+1 \leq i \leq n-m \\ 1 + \frac{n-i}{m} & \text{if } n-m+1 \leq i \leq n \end{cases}$$

To estimate the entropy in RSS scheme, we may note that the estimator of  $F^{-1}(i/n)$  must be positive for log function to be well-defined. So we have to order the ranked set sample. There are two ways to order this sample. First way is to order each replication, derive the estimator and then take the average as the main estimator. The second way is to order the whole sample of size  $rk$ . This two methods yield two estimators as follows

$$H_{mn}^1 = \frac{1}{n} \sum_{i=1}^n \log \frac{n}{c_i m} (X_{[i+m]} - X_{[i-m]}) \quad (6)$$

and

$$H_{mn}^2 = \frac{1}{n} \sum_{j=1}^r \sum_{i=1}^k \log \frac{k}{d_i m} (X_{[i+m]j} - X_{[i-m]j}), \quad (7)$$

Table 2: Monte Carlo biases and RMSE for  $H_{mn}^1$  in three distributions for  $n = 10, 20$ 

		U(0,1)				e(1)				N(0,1)			
		SRS		RSS		SRS		RSS		SRS		RSS	
$n$	$m$	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
10	1	-0.381	0.451	-0.259	0.326	-0.392	0.561	-0.298	0.398	-0.452	0.458	-0.342	0.428
	2	-0.222	0.293	-0.108	0.168	-0.222	0.436	-0.142	0.266	-0.342	0.441	-0.227	0.311
	3	-0.159	0.228	-0.070	0.124	-0.174	0.405	-0.078	0.241	-0.301	0.408	-0.207	0.289
	4	-0.140	0.224	-0.056	0.110	-0.114	0.382	-0.031	0.236	-0.305	0.394	-0.209	0.285
	5	-0.131	0.212	-0.050	0.107	-0.064	0.371	0.012	0.249	-0.289	0.389	-0.204	0.279
20*	1	-0.328	0.358	-0.274	0.302	-0.335	0.424	-0.290	0.340	-0.373	0.427	-0.313	0.358
	2	-0.176	0.203	-0.121	0.147	-0.179	0.299	-0.139	0.206	-0.221	0.288	-0.178	0.232
	3	-0.125	0.155	-0.076	0.103	-0.151	0.280	-0.083	0.169	-0.179	0.252	-0.141	0.200
	4	-0.104	0.134	-0.056	0.084	-0.098	0.264	-0.052	0.161	-0.176	0.255	-0.124	0.189
	5	-0.088	0.119	-0.046	0.074	-0.062	0.253	-0.024	0.157	-0.167	0.245	-0.117	0.184
	6	-0.079	0.117	-0.040	0.067	-0.047	0.244	0.001	0.165	-0.156	0.232	-0.116	0.185
	7	-0.076	0.111	-0.035	0.063	-0.020	0.263	0.025	0.173	-0.150	0.231	-0.116	0.185
	8	-0.068	0.109	-0.034	0.062	0.010	0.264	0.051	0.188	-0.157	0.239	-0.114	0.185
	9	-0.064	0.108	-0.032	0.063	0.032	0.260	0.078	0.203	-0.158	0.241	-0.116	0.188
	10	-0.061	0.106	-0.030	0.063	0.044	0.268	0.102	0.225	-0.152	0.234	-0.113	0.184

\* $n = 10r$  cases are observed by RSS scheme with 10 samples and  $r$  replication.

Table 3: Monte Carlo biases and RMSE for  $H_{mn}^1$  in three distributions for  $n = 30$ 

		U(0,1)				e(1)				N(0,1)			
		SRS		RSS		SRS		RSS		SRS		RSS	
$n$	$m$	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
30*	1	-0.312	0.337	-0.273	0.290	-0.293	0.363	-0.286	0.318	-0.328	0.370	-0.300	0.331
	2	-0.158	0.174	-0.125	0.141	-0.156	0.248	-0.136	0.181	-0.198	0.245	-0.160	0.199
	3	-0.110	0.129	-0.080	0.096	-0.115	0.219	-0.084	0.145	-0.158	0.209	-0.118	0.164
	4	-0.090	0.110	-0.058	0.075	-0.078	0.206	-0.052	0.129	-0.135	0.196	-0.099	0.150
	5	-0.071	0.092	-0.046	0.065	-0.059	0.202	-0.034	0.126	-0.113	0.184	-0.088	0.144
	6	-0.069	0.090	-0.039	0.058	-0.045	0.198	-0.013	0.125	-0.106	0.181	-0.082	0.142
	7	-0.061	0.083	-0.034	0.054	-0.023	0.206	0.004	0.129	-0.098	0.174	-0.073	0.138
	8	-0.056	0.079	-0.030	0.050	-0.007	0.194	0.021	0.135	-0.106	0.175	-0.069	0.138
	9	-0.052	0.076	-0.028	0.048	0.015	0.192	0.039	0.145	-0.086	0.174	-0.067	0.140
	10	-0.050	0.075	-0.027	0.046	0.027	0.195	0.057	0.155	-0.091	0.175	-0.067	0.141
	11	-0.048	0.075	-0.025	0.045	0.050	0.211	0.073	0.167	-0.091	0.171	-0.065	0.141
	12	-0.041	0.071	-0.024	0.045	0.075	0.225	0.098	0.185	-0.090	0.171	-0.062	0.141
	13	-0.042	0.074	-0.023	0.045	0.089	0.231	0.117	0.201	-0.089	0.175	-0.065	0.144
	14	-0.043	0.073	-0.022	0.046	0.100	0.248	0.132	0.214	-0.090	0.174	-0.066	0.143
	15	-0.037	0.069	-0.021	0.046	0.124	0.255	0.150	0.231	-0.094	0.177	-0.064	0.143

\* $n = 10r$  cases are observed by RSS scheme with 10 samples and  $r$  replication.

where

$$d_i = \begin{cases} 1 + \frac{i-1}{m} & \text{if } 1 \leq i \leq m \\ 2 & \text{if } m+1 \leq i \leq k-m \\ 1 + \frac{k-i}{m} & \text{if } k-m+1 \leq i \leq k \end{cases} .$$

Table 1 shows the values of simulated Minimum RMSE (MRMSE) and Minimum Absolute Bias (MAB) of  $H_{mn}^1$  and  $H_{mn}^2$  and optimal  $m$  for  $k = 10$  and three famous distributions with different values of  $r$ . From this values one can conclude that  $H_{mn}^1$  is better estimator in the sense of RMSE and bias. Tables 2 and 3 show the values of Monte Carlo biases and RMSE for  $H_{mn}^1$  in three distributions for  $n = 10, 20$  and  $30$ . This values present a distinct improvement of the estimator in RSS scheme relative to SRS scheme.

### 3 Goodness of fit tests

Park, S. and D. (2003) derived the nonparametric distribution function of  $H_c(n, m)$  as

$$g_c(x) = \begin{cases} 0 & \text{if } x < \eta_1 \quad \text{or} \quad x > \eta_{n+1} \\ n^{-1} \frac{1}{\eta_{i+1} - \eta_i} & \text{if } \eta_i < x \leq \eta_{i+1}, i = 1, \dots, n \end{cases} ,$$

where

$$\eta_i = \begin{cases} \xi_{m+1} - \sum_{k=i}^m \frac{1}{m+k-1} (x_{(m+k)} - x_{(1)}) & \text{if } 1 \leq i \leq m \\ \frac{1}{2m} (x_{(i-m)} + \dots + x_{(i+m-1)}) & \text{if } m+1 \leq i \leq n-m+1 \\ \xi_{n-m+1} + \sum_{k=n-m+2}^i \frac{1}{n+m-k+1} (x_{(n)} - x_{(k-m-1)}) & \text{if } n-m+2 \leq i \leq n+1 \end{cases}$$

They used it to correct the moments of the distribution which are used in goodness of fit tests.

In the exponentiality test, the aforementioned nonparametric distribution is used to estimate the mean and  $\hat{\lambda}_c$ .

$$I(g : f) = \int_{-\infty}^{\infty} g(x) \ln \frac{g(x)}{f(x)} dx \quad (8)$$

$$T_c = 1 + \log \hat{\lambda}_c - H_c(n, m) \quad (9)$$

The following alternatives of the exponentiality null hypothesis have been considered to estimate the powers.

1. Gamma distribution with pdf

$$f(x; \alpha) = \frac{x^{\alpha-1} \exp(-x)}{\gamma(\alpha)} \quad \alpha > 0, x > 0 \quad (10)$$

2. Weibull distribution with pdf

$$f(x; \beta) = \beta x^{\beta-1} \exp(-x^\beta) \quad \beta > 0, x > 0 \quad (11)$$

3. Log-normal distribution with pdf

$$f(x; \alpha) = \frac{1}{\sigma\sqrt{2\pi}x} \exp\left(-\frac{1}{2\sigma^2}(\log x)^2\right) \quad \sigma > 0, x > 0 \quad (12)$$

4. Uniform distribution with pdf

$$f(x) = 1 \quad 0 < x < 1 \quad (13)$$

As mentioned by Arizono and Ohta (1989), an estimate for  $I(f, f_0)$ , when  $f_0$  is the normal pdf with known parameters  $\mu$  and  $\sigma$  is obtained as

$$I_{mn} = \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2n} \sum_{i=1}^n \left( \frac{x_i - \mu}{\sigma} \right)^2 - H(n, m). \quad (14)$$

When both  $\mu$  and  $\sigma$  are unknown, we place their estimates, that is,  $\hat{\mu} = \bar{X}$  and  $\hat{\sigma} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$  in (29) and derive the test statistic as

$$T = \log(\sqrt{2\pi\hat{\sigma}^2}) + 0.5 - H(n, m) \quad (15)$$

Park, S. and D. replaced the estimates  $H(n, m)$  and  $\hat{\sigma}$  with their corrected estimators  $H_c(n, m)$  and  $\hat{\sigma}_c$  and derived the test statistic

$$T_c = \log(\sqrt{2\pi\hat{\sigma}_c^2}) + 0.5 - H_c(n, m) \quad (16)$$

In the normality test the following alternatives are considered to estimate the powers

1. Uniform distribution with pdf

$$f(x) = 1 \quad 0 < x < 1 \quad (17)$$

2. Chi-square distribution with pdf

$$f(x; \alpha) = \frac{1}{\Gamma(\alpha/2)} \left(\frac{1}{2}\right)^{\alpha/2} x^{(\alpha/2)-1} \exp\left(-\frac{1}{2}x\right) \quad \alpha > 0, x > 0 \quad (18)$$

3. t-student distribution with pdf

$$f(x; \nu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)} \frac{1}{\sqrt{(\nu\pi)}} \frac{1}{(1+x^2)^{(\nu+1)/2}} \quad \nu > 2, -\infty < x < \infty \quad (19)$$

4. Exponential distribution with pdf

$$f(x; \lambda) = \lambda \exp(-\lambda x), \quad \lambda > 0, x > 0. \quad (20)$$

Table 4: Critical values for different values of  $n$ ,  $m$  and  $\alpha$   
Exponentiality Normality

$n$	$m$	$\alpha$				$\alpha$			
		0.1	0.05	0.025	0.01	0.1	0.05	0.025	0.01
10	1	0.5357	0.6318	0.7297	0.8617	0.5898	0.7027	0.8034	0.9215
	2	0.2898	0.3546	0.4213	0.5099	0.3765	0.4404	0.5113	0.6005
	3	0.2095	0.2645	0.3243	0.3944	0.3214	0.3712	0.4182	0.4667
	4	0.1619	0.2154	0.2596	0.3293	0.3001	0.3221	0.3593	0.3987
	5	0.1416	0.1916	0.2487	0.3122	0.2903	0.3091	0.3311	0.3544
20*	1	0.4455	0.5091	0.5695	0.6373	0.4775	0.5405	0.6025	0.6587
	2	0.2391	0.2822	0.3305	0.3813	0.2824	0.3264	0.3621	0.4092
	3	0.1707	0.2089	0.2450	0.2939	0.2296	0.2614	0.2940	0.3460
	4	0.1389	0.1738	0.2064	0.2498	0.2073	0.2339	0.2671	0.3112
	5	0.1117	0.1445	0.1772	0.2173	0.2000	0.2287	0.2549	0.2875
	6	0.0964	0.1269	0.1569	0.1918	0.1977	0.2255	0.2501	0.2802
	7	0.0779	0.1114	0.1441	0.1741	0.1968	0.2223	0.2463	0.2695
	8	0.0643	0.0983	0.1250	0.1754	0.2013	0.2225	0.2407	0.2612
	9	0.0495	0.0915	0.1188	0.1604	0.2023	0.2213	0.2375	0.2569
	10	0.0368	0.0797	0.1167	0.1543	0.2008	0.2175	0.2391	0.2512
30*	1	0.4100	0.4567	0.4961	0.5656	0.4273	0.4729	0.5155	0.5768
	2	0.2171	0.2498	0.2796	0.3156	0.2443	0.2776	0.3028	0.3451
	3	0.1516	0.1819	0.2122	0.2402	0.1891	0.2145	0.2408	0.2777
	4	0.1202	0.1481	0.1693	0.2065	0.1649	0.1855	0.2099	0.2407
	5	0.0979	0.1210	0.1503	0.1860	0.1498	0.1739	0.1912	0.2300
	6	0.0825	0.1102	0.1361	0.1559	0.1454	0.1658	0.1879	0.2208
	7	0.0722	0.0950	0.1212	0.1501	0.1433	0.1660	0.1891	0.2134
	8	0.0574	0.0849	0.1061	0.1449	0.1425	0.1663	0.1848	0.2082
	9	0.0574	0.0849	0.0960	0.1270	0.1453	0.1631	0.1833	0.2046
	10	0.0379	0.0635	0.0878	0.1162	0.1428	0.1654	0.1838	0.2039
	11	0.0280	0.0545	0.0760	0.1097	0.1468	0.1661	0.1838	0.2056
	12	0.0151	0.0447	0.0706	0.1030	0.1489	0.1697	0.1875	0.2049
	13	0.0043	0.0354	0.0640	0.0927	0.1502	0.1719	0.1891	0.2072
	14	-0.0046	0.0274	0.0612	0.0882	0.1527	0.1720	0.1857	0.2073
	15	-0.0190	0.0182	0.0505	0.0813	0.1492	0.1716	0.1871	0.2091

cases are observed by RSS scheme with 10 samples and  $r$  replication.



Stokes (1980) proposed the sample variance as an estimator of the population variance as follows

$$\hat{\sigma}^2 = \frac{1}{rk-1} \sum_{i=1}^r \sum_{j=1}^k (X_{[j]i} - \hat{\mu})^2 \quad (21)$$

This estimator is asymptotically unbiased and asymptotically more efficient than the sample variance in SRS. MacEachern et al. (2002) proposed an unbiased estimator of the variance as follows

$$\tilde{\sigma}^2 = \frac{1}{rk} (k-1) \text{MST} + (rk-k+1) \text{MSE}, \quad (22)$$

where

$$\text{MST} = \frac{1}{k-1} \sum_i \sum_j (X_{j[i]} - \hat{\mu})^2 - \frac{1}{k-1} \sum_j \sum_i (X_{j[i]} - \bar{X}_{[j].})^2, \quad (23)$$

$$\text{MSE} = \frac{1}{k(r-1)} \sum_j \sum_i (X_{[j]i} - \bar{X}_{[j].})^2, \quad (24)$$

$$\bar{X}_{[j].} = \sum_i X_{[j]i} / r. \quad (25)$$

and

$$\hat{\mu} = \sum_i \sum_j X_{[j]i} / rk. \quad (26)$$

If we use our entropy estimator for estimation of Kullback-Leibler distance between an unknown pdf and the pdf of the normal distribution, we derive

$$KL_{mn} = \log(\sqrt{2\pi\sigma^2}) + \frac{1}{2n} \sum_{i=1}^n \left( \frac{x_i - \mu}{\sigma} \right)^2 - H_{mn}^2. \quad (27)$$

In goodness of fit test of normality when  $\mu$  and  $\sigma$  are unknown we can place their estimators in the RSS scheme, i.e.  $\hat{\mu}$  in (26) and the Stokes estimator, (21) to derive the test statistic as

$$KL_{mn}^1 = \log(\sqrt{2\pi\hat{\sigma}^2}) + 0.5 - H_{mn}^2. \quad (28)$$

If we place the MacEachern et al. estimator of variance in (27), we derive another test statistic as

$$KL_{mn}^2 = \log(\sqrt{2\pi\tilde{\sigma}^2}) + \frac{1}{2n} \sum_{i=1}^n \left( \frac{x_i - \hat{\mu}}{\tilde{\sigma}} \right)^2 - H_{mn}^2. \quad (29)$$

Table 4 contains critical values of exponentiality and normality tests for different values of  $n$ ,  $m$  and  $\alpha$ .

Table 5 propose a comparison of powers in RSS and SRS schemes, for exponentiality and normality tests. The SRS values of powers are given from Park. S. and D. with the modified sample entropy of Ebrahimi et al. and their modified estimators of moments. We used the similar window size  $m$  for the comparison although our maximum powers may be obtained for different

Table 5: Power comparison of 0.05 tests against some alternatives in SRS and RSS schemes

Exponentiality						
Alternatives	$n$					
	20*		50*			
	$(m = 4)$		$(m = 6)$			
	SRS	RSS	SRS	RSS		
Gamma (1.5)	0.2176	0.2740	0.3480	0.4193		
Lognormal (1)	0.2685	0.1908	0.6613	0.4156		
Weibull (1.5)	0.4639	0.6199	0.7752	0.9056		
Gamma (2)	0.4862	0.6218	0.8281	0.9050		
Gamma (3)	0.8816	0.9693	0.9993	0.9999		
Uniform	0.8021	0.9979	0.9989	1.0000		
Weibull (2)	0.9138	0.9896	0.9995	1.0000		
Lognormal (0.5)	0.9967	0.9994	1.0000	1.0000		
Average power	0.6288	0.7078	0.8263	0.8307		
Normality						
Alternatives	$n$					
	20*		50*			
	$(m = 3)$		$(m = 4)$			
	SRS	RSS	SRS	RSS		
	$KL_{mn}^2$	$KL_{mn}^1$	$KL_{mn}^2$	$KL_{mn}^1$		
t(5)	0.1069	0.0847	0.0865	0.2395	0.1515	0.1497
t(3)	0.1989	0.1761	0.1748	0.5132	0.4009	0.3868
Uniform	0.3851	0.4801	0.4897	0.8850	0.9843	0.9800
$\chi_4^2$	0.5058	0.5704	0.5739	0.9326	0.9709	0.9710
$\chi_2^2$ (Exponential)	0.8656	0.9574	0.9650	0.9997	1.0000	1.0000
$\chi_1^2$	0.9934	0.9999	0.9999	1.0000	1.0000	1.0000
Average power	0.5093	0.5448	0.5483	0.5713	0.7513	0.7479

\* $n = 10r$  cases are observed by RSS scheme with 10 samples and  $r$  replication.

Table 6: Maximum powers (maximal  $m$ ) of 0.05 tests against some alternatives of the null hypothesis distributions

Exponentiality					
<i>Alternatives</i>	<i>n</i>				
	10	20*	30*	40*	50*
Gamma (1.5)	0.5760(5)	0.3761(8)	0.4126(12)	0.4371(14)	0.4569(7)
Lognormal (1)	0.1333(2)	0.2140(3)	0.3133(3)	0.4143(4)	0.5174(3)
Weibull (1.5)	0.5999(5)	0.7600(8)	0.8365(15)	0.8725(8)	0.9099(7)
Gamma (2)	0.5638(4)	0.7216(8)	0.7939(7)	0.8570(8)	0.9153(7)
Gamma (3)	0.9023(5)	0.9745(5)	0.9956(5)	0.9997(5)	1.0000(3-5)
Uniform	0.9201(5)	1.0000(8,10)	1.0000(3-15)	1.0000(2-20)	1.0000(2-25)
Weibull (2)	0.9659(5)	0.9963(8)	0.9998(8,12)	1.0000(4-12)	1.0000(3-12)
Lognormal (0.5)	0.9815(4)	0.9995(3)	1.0000(2-6)	1.0000(2-9)	1.0000(2-12)
Normality					
<i>Alternatives</i>	<i>n</i>				
	10	20*	30*	40*	50*
t(5)	0.0813(4)	0.0865(3)	0.1133(3)	0.1427(2)	0.1615(2)
t(3)	0.1335(4)	0.1846(2)	0.2820(2)	0.3514(3)	0.4260(3)
Uniform	0.1523(2)	0.5805(10)	0.9036(11)	0.9875(16)	0.9992(16,20)
$\chi_4^2$	0.3462(4)	0.6164(4)	0.8305(6)	0.9334(6)	0.9781(5)
$\chi_2^2$ (Exponential)	0.6926(4)	0.9670(4)	0.9992(4)	1.0000(3-8)	1.0000(1-14)
$\chi_1^2$	0.9492(3)	0.9999(3-5)	1.0000(1-12)	1.0000(1-17)	1.0000(1-22)

\* $n = 10r$  cases are observed by RSS scheme with 10 samples and  $r$  replication.

values of  $m$ . For normality test two test statistics  $KL_{mn}^1$  and  $KL_{mn}^2$  are compared in the sense of power. For  $n = 20$ , using the statistic  $KL_{mn}^2$  cause less powers than  $KL_{mn}^1$ . Although the average of powers of  $KL_{mn}^2$  gets larger than the average power of  $KL_{mn}^1$  when  $n$  increases to 50, but the difference between this powers is ignorable. Since obtaining the statistic  $KL_{mn}^2$  is more complicated than  $KL_{mn}^1$ , we prefer to use  $KL_{mn}^1$  for the remaining of the study.

Table 6 shows the maximum powers and the maximal window size,  $m$  for  $\alpha = 0.05$  of exponentiality and normality tests. Ebrahimi et al. (1992) used such maximality to obtain some optimal window size  $m$  for each  $n$ . Table 6 shows that here this values of optimal  $m$  differs distinctly for different alternatives. In fact choosing an optimal  $m$  depends very closely to the alternative which is unknown. So in this paper we use the average of powers for considered alternatives as a measure to decide about the optimal  $m$ . The values of average powers are tabulated in Table 7. The authors believe that this values are more useful for the experimenter who wants to perform a test, since he is not aware about the alternative. Table 8 shows the optimal  $m$  and the maximum average powers for different values of  $n$  of exponentiality and normality tests.

Table 7: Average powers  $\alpha = 0.05$  for different alternatives and different values of  $n$  and  $m$

Exponentiality														
$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP
10	1	0.2905	30*	1	0.5470	40*	1	0.6156	40*	16	0.7692	50*	11	0.7997
	2	0.5138		2	0.6851		2	0.7325		17	0.7643		12	0.7950
	3	0.6281		3	0.7364		3	0.7786		18	0.7634		13	0.7872
	4	0.6939		4	0.7564		4	0.8026		19	0.7647		14	0.7866
	5	0.7009		5	0.7759		5	0.8067		20	0.7551		15	0.7836
20*	1	0.4477		6	0.7640		6	0.8056	50*	1	0.6509		16	0.7802
	2	0.6245		7	0.7685		7	0.7972		2	0.7628		17	0.7772
	3	0.6845		8	0.7630		8	0.7970		3	0.8207		18	0.7749
	4	0.7078		9	0.7447		9	0.7872		4	0.8334		19	0.7755
	5	0.7277		10	0.7634		10	0.7838		5	0.8392		20	0.7725
	6	0.7342		11	0.7598		11	0.7786		6	0.8307		21	0.7696
	7	0.7382		12	0.7591		12	0.7732		7	0.8308		22	0.7672
	8	0.7406		13	0.7553		13	0.7766		8	0.8184		23	0.7722
	9	0.7321		14	0.7521		14	0.7732		9	0.8142		24	0.7709
	10	0.7259		15	0.7504		15	0.7662		10	0.8042		25	0.7660
Normality														
$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP	$n$	$m$	AP
10	1	0.2765	30*	1	0.5229	40*	1	0.5776	40*	16	0.6098	50*	11	0.6746
	2	0.3470		2	0.6154		2	0.6811		17	0.5960		12	0.6702
	3	0.3622		3	0.6547		3	0.7130		18	0.5808		13	0.6647
	4	0.3876		4	0.6628		4	0.7173		19	0.5702		14	0.6583
	5	0.3520		5	0.6559		5	0.7072		20	0.5540		15	0.6517
20*	1	0.4276		6	0.6518		6	0.6995	50*	1	0.6375		16	0.6457
	2	0.5141		7	0.6361		7	0.6911		2	0.7269		17	0.6385
	3	0.5483		8	0.6219		8	0.6786		3	0.7482		18	0.6325
	4	0.5586		9	0.6226		9	0.6689		4	0.7479		19	0.6227
	5	0.5418		10	0.6104		10	0.6598		5	0.7415		20	0.6160
	6	0.5294		11	0.5983		11	0.6521		6	0.7283		21	0.6090
	7	0.5230		12	0.5799		12	0.6425		7	0.7148		22	0.5952
	8	0.5078		13	0.5631		13	0.6363		8	0.7043		23	0.5858
	9	0.4891		14	0.5505		14	0.6258		9	0.6903		24	0.5713
	10	0.4744		15	0.5291		15	0.6168		10	0.6827		25	0.5592

\* $n = 10r$  cases are observed by RSS scheme with 10 samples and  $r$  replication.

Table 8: Values of the window size  $m$  with largest average of powers against alternatives

$n$	Optimal $m$ (max average power)	
	Exponentiality	Normality
10	5(0.7009)	4(0.3876)
20	8(0.7406)	4(0.5586)
30	5(0.7759)	4(0.6628)
40	5(0.8067)	4(0.7173)
50	5(0.8392)	3(0.7482)

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